Quantifying radiative perturbations from observations

and application to the short-term water vapor feedback

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  1. Partial radiative perturbation (PRP) calculations: calculations that substitutes one-at-a-time a variable from the perturb climate into the control climate.
     (Wetherald and Manabe 1988)
  2. Radiative kernels: separates the radiative response and the perturbations
     (Held and Soden 2000; Soden and Held 2006; Soden et al. 2008)
     - Fewer computations: a single radiative calculation can be consistently applied across different climate models.
     - Radiative kernel have become an indispensable tool for GCM feedback studies

Observed radiative perturbations

- GCM-derived radiative kernels also been applied to observations in attempt to constrain climate feedbacks (Dessler 2008, 2010, 2013; Dessler and Wong 2009; Masters 2012; Dessler and Loeb 2013; Gordon et al. 2013, Zhou et al. 2013, 2014; Ceppi 2016)
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- **Limited comparisons of GCM vs. observational-based kernels**
  (different GCM kernels show relatively small differences)
- **Would be attractive to perform calculations based purely on observations**

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- Provide general insight into the variability of the radiation budget
  - Useful where radiative effects are correlated among parameters.
    - E.g. clouds: compliment to the cloud radiative effect (CRE, total - clear-sky fluxes)

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- Easy to incorporate multiple datasets for each input

PRP calculations

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$$\partial F^{f}_{\Delta x} = F(x, y_1, ..., y_N) - F(\overline{x}, y_1, ..., y_N) \quad (1)$$

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$$\partial F^f_{\Delta x} = F(x, y_1, ..., y_N) - F(\overline{x}, y_1, ..., y_N) + O^f(\Delta x) \tag{1}$$

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- From monthly-mean inputs, climatologies are constructed and the variables combined to make the 4 sets of inputs → Fu-Liou radiative model

Inputs (mostly) from CERES datasets

- Clear-sky: **GEOS** | **AIRS** (AIRX3STM)
  temperature, water vapor, ozone, skin temperature
- Clouds: **SYN** | **C3M**
  fraction, base, top, phase, optical depth, size
- Aerosol: **MATCH**
  optical depth, vertical distribution, type
- Gases: **AIRS** (AIRS3C2M/AIRX3STM)
  carbon dioxide, methane
- Gases: **NOAA ESRL** (global means)
  nitrous oxide, CFC-11, CFC-12, HCFC-22
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Focus here on 13 years of SYN + GEOS/AIRS (Sept. 2002 – Aug. 2015)

Validation

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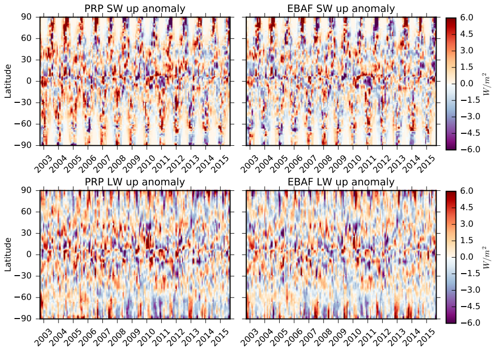
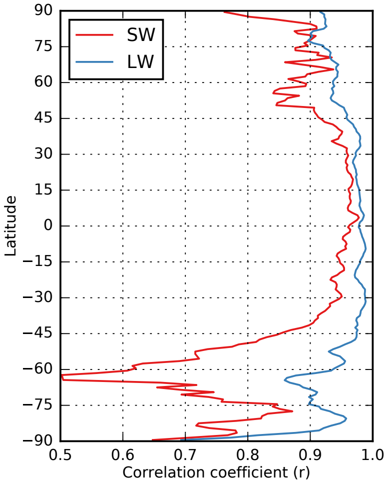
❸ Reproduce the variability as observed by CERES

- Time series well correlated over much of the globe (expect $\sim 60°$S)





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- Compute monthly perturbation to TOA flux caused by tropospheric water vapor: ΔF
- Feedback = slope of least-squares fit of ΔF and surface temperature anomaly

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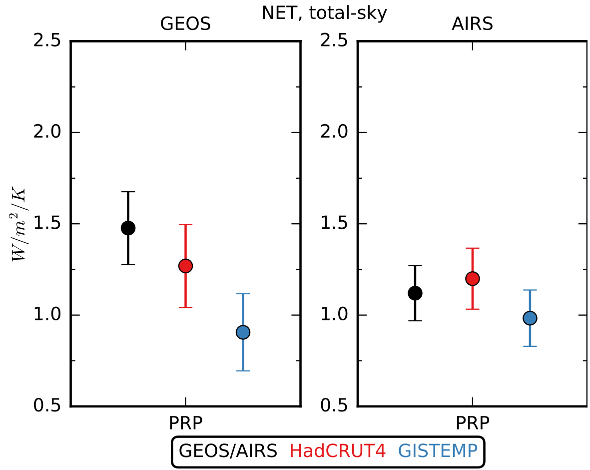

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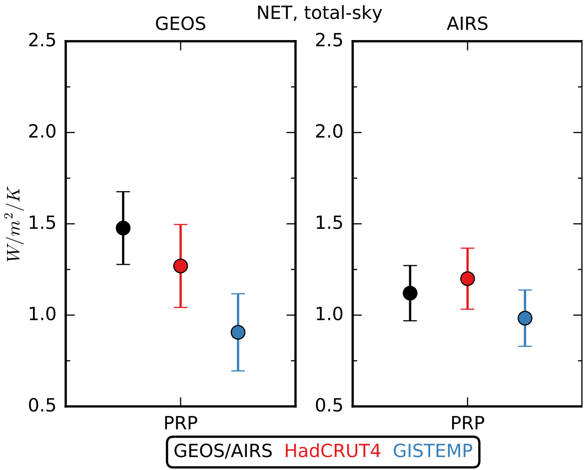

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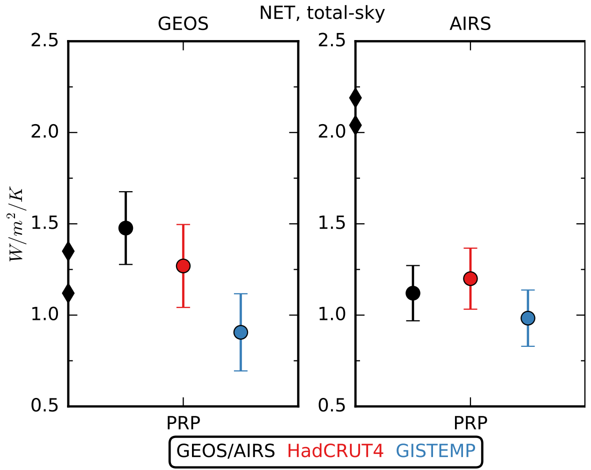

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- GEOS in agreement with previous reanalysis estimates
- **AIRS feedback nearly half that of previous estimates**
  - D08/G13: different period of data, older versions of datasets, kernels for getting ΔF

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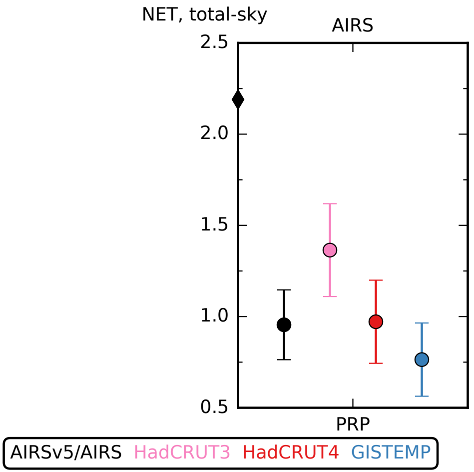

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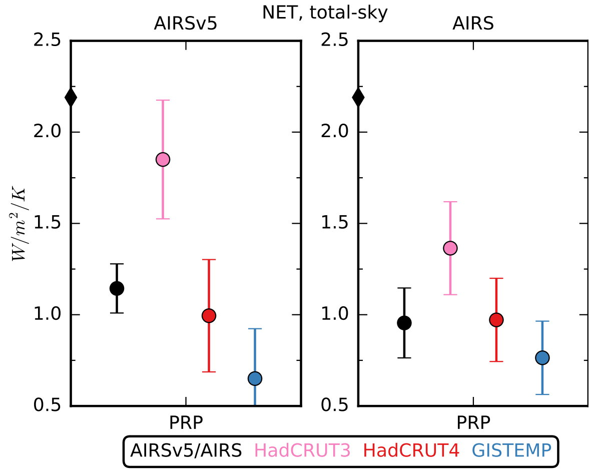

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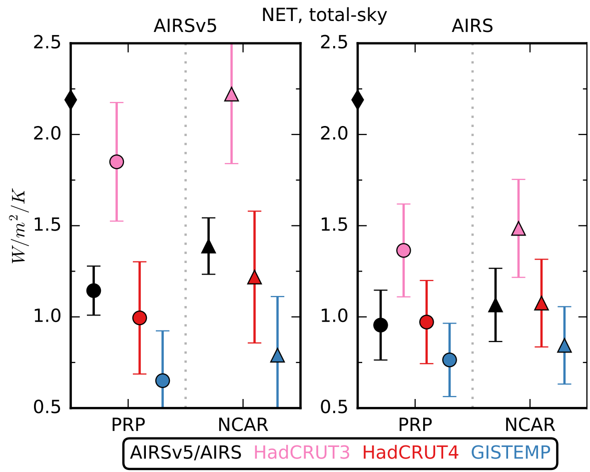

- AIRSv6 feedback smaller than full time series
- HadCRUT3 give largest feedback
- AIRSv5 + HadCRUT3 = largest feedback
- AIRSv5 + HadCRUT3 + NCAR kernel (Shell et al. 2008) ≈ G13
    - AIRSv6/HadCRUT4 increase yield/coverage

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- Older water vapor feedback estimates using AIRSv5 + HadCRUT3 nearly 2x larger: mostly due to dataset updates (also differences from kernel, length of data)

Looking forward:

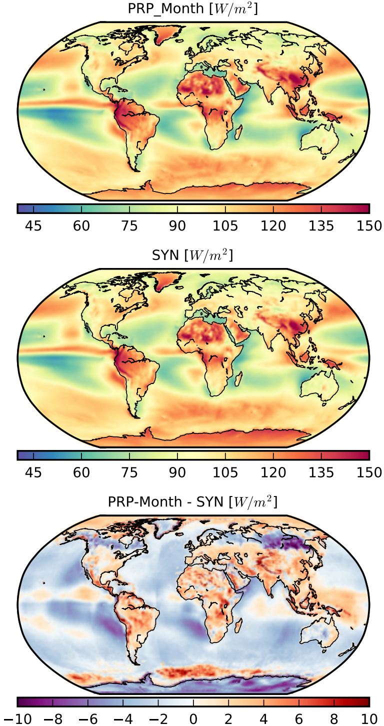
- AIRS v6.1: overhaul of water vapor retrievals
- Interesting to perform calculations with active sensor clouds (C3M)
  (likely to decrease water vapor feedback a bit)
- CERES-optimized radiative kernels: “two-pass” calculation to require that the sum of individual flux anomalies match CERES
  (similar to Sanderson and Shell 2012)

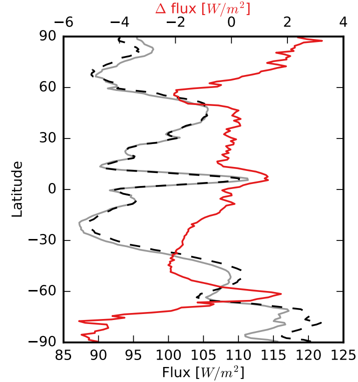
Use of monthly mean inputs

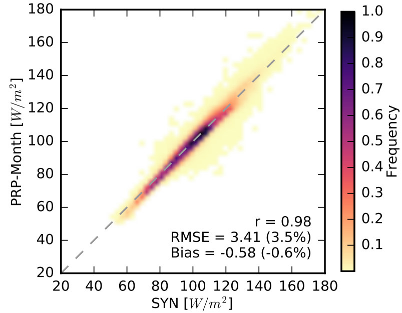
Fluxes from monthly-mean inputs (**PRP_Month**) vs. average fluxes computed in **SYN**

- Good agreement: -0.6, -1.8 W/m^2 (SW, LW)
- SYN CERES-derived fluxes:(not shown) +0.8, -3.6 W/m^2 (SW, LW)

TOA total SW up







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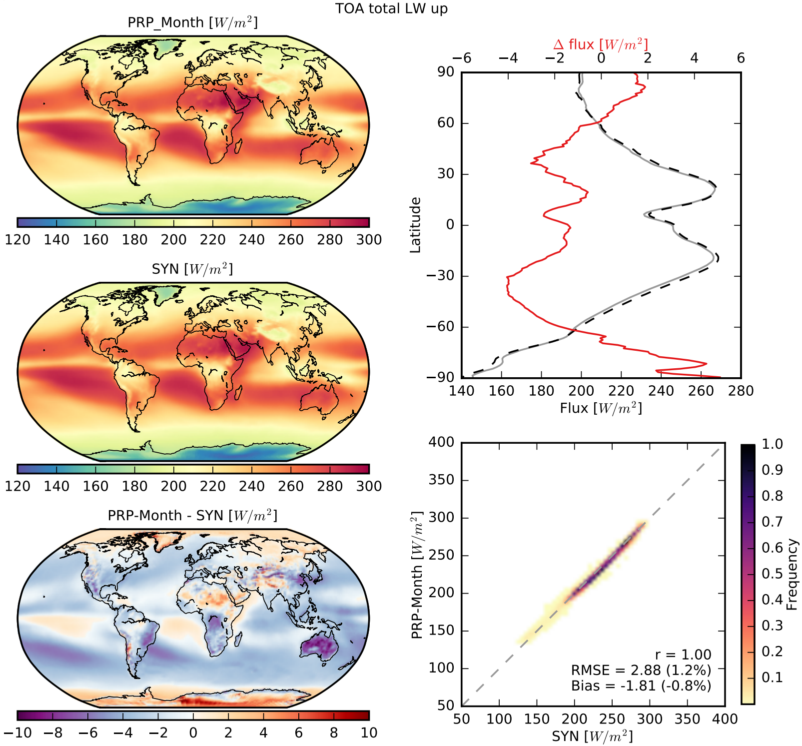
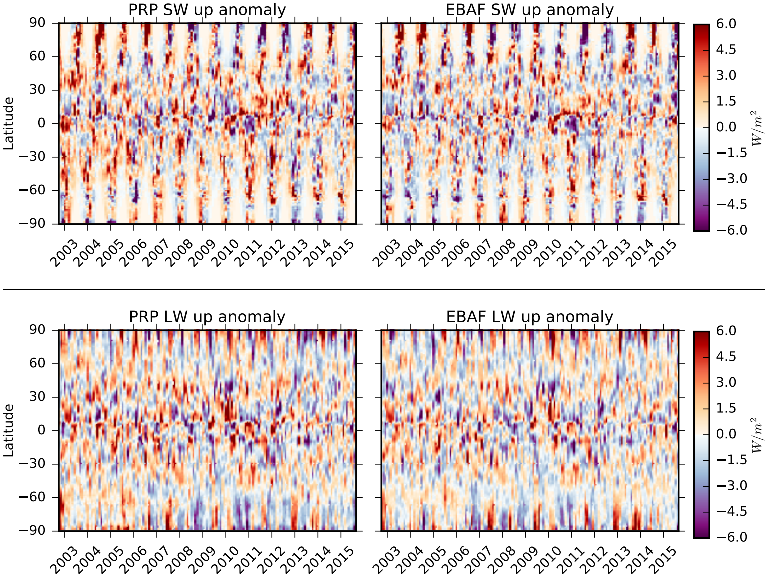
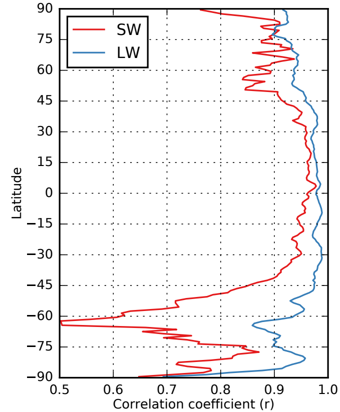


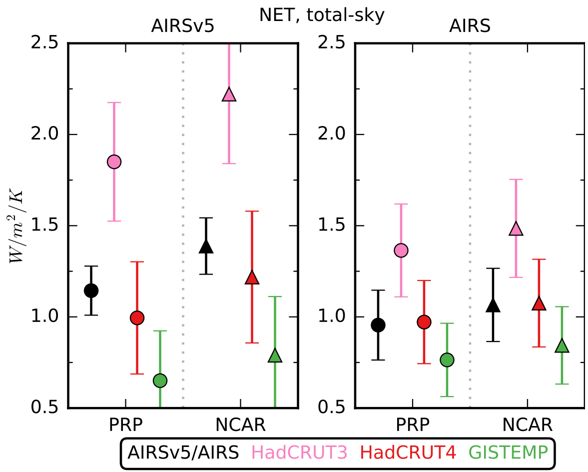
Comparison to CERES (EBAF)





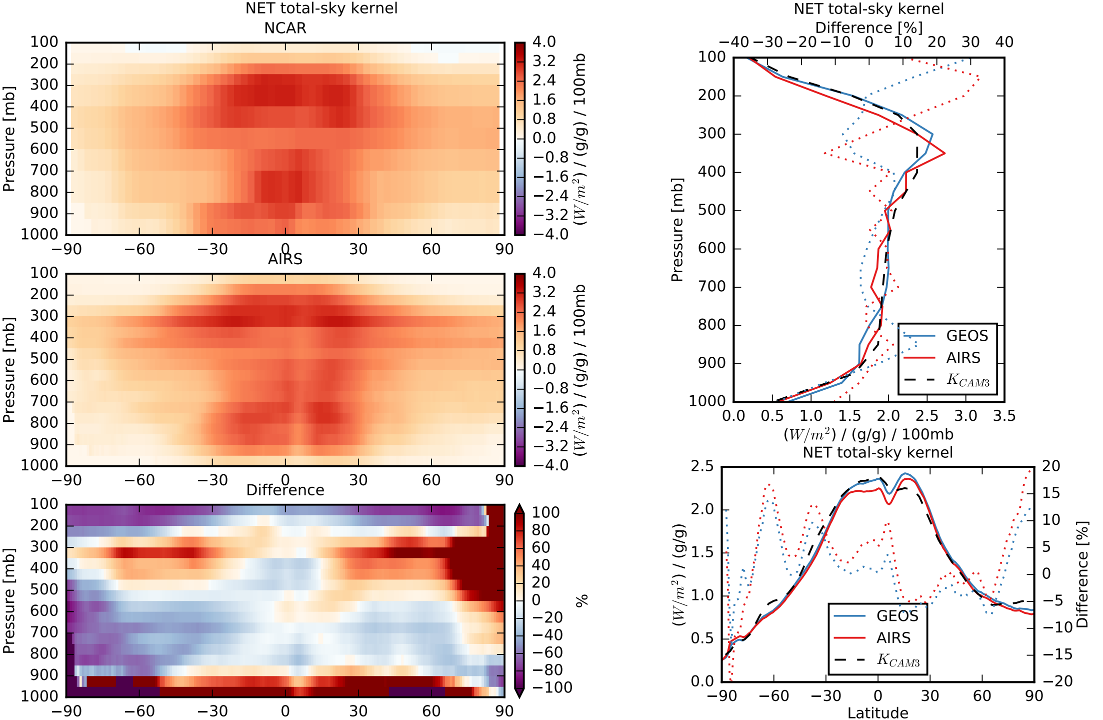
- Time series well correlated over much of the globe
- 60°S: ??

Comparison to NCAR kernel



- Using NCAR kernel give a (slightly) larger feedback
- Kernel differences: (not shown)
  - Zonal / vertical means: $\sim 10\%$
    (about the same as among different GCMs (Soden et al. 2008))
  - Local differences: ~ 20–40%
    (larger than among different GCMs (Soden et al. 2008))

Comparison to NCAR kernel (Shell et al. 2008)



Short vs. Long-term water vapor feedback

- Gordon et al. (2013): short-term feedbacks in CMIP3 models converge to 15% of their long-term value after 25 years